Strategic Management Journal
Strat. Mgmt. J., **32**: 569–594 (2011)
Published online EarlyView in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/smj.899
Received 24 September 2008; *Final revision received 8 October 2010*

MENTAL MODELS, DECISION RULES, AND PERFORMANCE HETEROGENEITY

MICHAEL SHAYNE GARY[1]* and ROBERT E. WOOD[2]
[1] *Australian School of Business, University of New South Wales, Sydney, New South Wales, Australia*
[2] *Melbourne Business School, Carlton, Victoria, Australia*

This paper focuses on the role of managerial cognition as a source of heterogeneity in firm strategies and performance. We link differences in mental models to differences in decision rules and performance in a management simulation. Our results show more accurate mental models lead to better decision rules and higher performance. We also find that decision makers do not need accurate knowledge of the entire business environment; accurate mental models of the key principles are sufficient to achieve superior performance. A fundamental assumption in much of strategic management is that managers who have a richer understanding about organizational capabilities and the dynamics of industry structure can improve the performance of their firms. Our findings provide empirical evidence supporting this assumption and show that differences in mental models help explain ex ante why managers and firms adopt different strategies and achieve different levels of competitive success.

INTRODUCTION

Understanding why some firms and not others adopt strategies ultimately associated with competitive success is of central importance to strategy scholars. In addressing one aspect of this issue, research examining the role of managerial cognition has shown that managerial mental models are a critical determinant of strategic choices (Gavetti, 2005; Kaplan and Tripsas, 2008; Porac, Thomas, and Baden-Fuller, 1989; Reger and Huff, 1993; Simon, 1991; Walsh, 1995). Managerial mental models are simplified knowledge structures or cognitive representations about how the business environment works. There is substantial evidence that mental models influence decision making through managers' efforts to match strategic choices to their understanding of the business environment (Barr, Stimpert, and Huff, 1992; Porac *et al*., 1995; Tripsas and Gavetti, 2000). There is limited empirical evidence, however, for the link between mental model accuracy and performance.

Advancing our knowledge about the relationship between mental model accuracy and performance is important. There are strong beliefs within strategic management that managers who have a richer understanding about the dynamics of industry structure and organizational capabilities can improve the performance of their firms (Cockburn, Henderson, and Stern, 2000). An alternative possibility is that complexity, uncertainty, and change in business environments overwhelm managers' capacity to take advantage of any richer understanding about the situation. Under such circumstances, competitive advantage would be driven by initial conditions, random environmental shocks, and lucky managerial responses rather than the

Keywords: mental models; decision rules; cognitive frames; heuristics; knowledge representations; schema
*Correspondence to: Michael Shayne Gary, Australian School of Business, University of New South Wales, Sydney NSW 2052, Australia. E-mail: sgary@unsw.edu.au

result of accurate mental models underpinning managerial foresight or strategic insights (Stinchcombe, 2000). There has been very little empirical research examining whether managers with more accurate mental models of the business environment achieve superior performance outcomes.

This paper reports the results from an experimental study examining the relationships between differences in mental model accuracy and performance. We also investigate the impact of partial knowledge—in contrast to accurate mental models of the complete business environment—on performance outcomes. Recent simulation-based research suggests that even partial knowledge of the business environment may dramatically improve performance (Denrell, Fang, and Levinthal, 2004; Gavetti and Levinthal, 2000), but thus far we have scarce empirical evidence. To better understand the connection between mental models and performance outcomes, we also examine the relationship between mental model accuracy and the quality of decision rules. In the face of complexity and uncertainty, managers adopt rules of thumb and heuristics that are intended to be consistent with their simplified mental models of the business environment (Cyert and March, 1992; Levitt and March, 1988; March and Simon, 1958; Nelson and Winter, 1982; Simon, 1991).

In the experiment, we utilize a management simulation to investigate these relationships in a controlled setting. This enables us to investigate mental models and decision rules in a complex decision environment using an experimental design that allows more precise measures of constructs and tests of hypothesized causal relationships. Our analyses highlight several features of mental models and decision making not studied in previous research. The findings show that accurate mental models about causal relationships in the business environment result in superior performance outcomes. This provides systematic evidence that accurate mental models are an important source of superior performance outcomes in complex environments. Our results also show that decision makers do not need accurate mental models of the entire business environment, but rather an accurate understanding of the key principles of deep structure. We also find that decision makers with more accurate mental models are more likely to adopt higher quality decision rules. The different decision rules cluster into a relatively small number of distinct strategies, and these strategies are significantly related to mental model accuracy and performance. Connecting heterogeneity in mental model accuracy to differences in decision rules and strategies contributes to our understanding about how and why strategic decisions emerge as they do and why managers adopt different strategies.

THEORY AND HYPOTHESES

Managers have limited information processing capabilities and rely on simplified mental models of reality to organize their knowledge and make sense of the world (Cyert and March, 1992; March and Simon, 1958). Research in psychology shows that these knowledge structures impact perception, information processing, problem solving, judgment, learning, and decision making (e.g., Anderson, 1990; Johnson-Laird, 1983; Rehder, 2003). Prior research spanning psychology, administrative and organization theory, economics, political science, computer science, and cognitive science has used a variety of terms for these knowledge structures including: mental models, schemas, dominant logics, causal maps, cognitive maps, frames, and belief systems (Axelrod, 1976; Bettis and Prahalad, 1995; Hodgkinson, Maule, and Bown, 2004; Huff, 1990; Simon, 1991; Sterman, 1989b).

Management research provides extensive evidence that managerial mental models are heterogeneous and affect strategic choices (Barr *et al.*, 1992; Eden and Spender, 1998; Gavetti, 2005; Gavetti and Levinthal, 2000; Hodgkinson *et al.*, 1999; Huff, 1990; Jackson and Dutton, 1988; Kaplan and Tripsas, 2008; Porac *et al.*, 1989; Reger and Huff, 1993; Simon, 1991; Tripsas and Gavetti, 2000; Walsh, 1995). Much of the strategy research examining the content of mental models has focused on how managers perceive and categorize information about their organization or competitive environment (Hodgkinson and Johnson, 1994; Jackson and Dutton, 1988; Porac *et al.*, 1995; Porac *et al.*, 1989; Reger and Huff, 1993). In contrast, there has been very little research investigating decision makers' mental models of the causal relationships in business environments and how these affect strategic choices. Recent research in psychology provides strong evidence that beliefs about cause-effect relationships are particularly important in supporting strategic decision making since they serve as the basis on which decision makers infer the consequences of their actions and

DOI: 10.1002/smj

guide intervention efforts to reach desired targets (Rehder, 2003). For example, solving complex strategic problems requires managers to generate options about where and how to intervene in their business by forming expectations about the possible outcomes that will result from their decisions. This process of developing strategic prescriptions relies heavily on the inferred causal relationships that make up managers' mental models about their business environment. Therefore, it is crucial to examine decision makers' inferences about chains of cause-effect relationships linking specific decision options to outcomes in order to understand how managers make strategic decisions (Levitt and March, 1988).

Prior research on managerial cognition has also established that different managers often perceive the same objective business environment differently (Barr *et al.*, 1992; Bourgeois, 1985; Tripsas and Gavetti, 2000). Despite strong evidence of heterogeneity in mental models, there has been very little strategy research that investigates the importance of accurate mental models on performance outcomes. This is surprising since a fundamental assumption in much of strategic management is that successful firms and managers purposefully adopt strategies—based on accurate mental models—that match or 'fit' the competitive environment. Most strategy scholars believe that managers who have a richer understanding of the dynamics of industry structure and organizational capabilities can take advantage of this knowledge to improve firm performance. Strategy courses at business schools are built on the basic idea that managers can advance their understanding (i.e., mental models) of the business environment through rigorous, disciplined analysis, and that these richer mental models will facilitate the development of winning strategies. 'The worth of a strategy depends on management's ability to... identify and to evaluate correctly the [business] environment' (Hatten and Schendel, 1976: 196). However, we have little systematic evidence that this is true (Henderson, 2000).

An alternative explanation is that the success or failure of individual firms is primarily driven by initial conditions, random shocks, and luck (Stinchcombe, 2000). This could be the case if resource positions are randomly distributed among firms during founding and any initial advantages are maintained through unyielding path dependence. This alternative might also be the dominant explanation for performance heterogeneity if managers are so completely overwhelmed by the complexity, uncertainty, and dynamism of the business environment to the point that strategic choices are equivalent to gambles at the racetrack (Stinchcombe, 2000). In other words, performance differences among firms may simply be a function of the realized competitive environment favoring some resource positions and some strategies above others.

There is some evidence from fieldwork as well as limited empirical support that accuracy of managerial mental models plays an important role in firm success (Barr *et al.*, 1992; Bourgeois, 1985; Tripsas and Gavetti, 2000). In addition, recent simulation-based work suggests that more accurate mental models about the causal relationships linking actions to outcomes translate into better performance (Denrell *et al.*, 2004) and may play a central role in the discovery of superior strategic positions (Gavetti and Levinthal, 2000; Gavetti, Levinthal, and Rivkin, 2005). On the other hand, Weick speculates that 'Accuracy [in mental models] is nice, but not necessary' (Weick, 1990: 6). Similarly, Sutcliffe (1994) suggests that inaccurate perceptions may lead to positive consequences for organizations if they enable managers to overcome inertial tendencies and propel them to pursue goals that might look unattainable when the environment is assessed accurately. In this line of reasoning, having an accurate mental model may be less important than having some mental map that brings order to the world and enables incremental and adaptive action.

Overall, prior strategy research suggests that accurate mental models are important, but no prior studies have empirically tested the value of mental model accuracy about the causal relationships of the business environment. Given the importance of this issue for strategic management, we need to improve our understanding about whether more accurate mental models enable managers *ex ante* to identify and interpret signals from their business environment that lead to superior strategic choices and performance outcomes.

We investigate this issue directly in this paper. Based on the research streams discussed above, we expect variation in the accuracy of decision makers' mental models as a result of their own individual, unique experiences and due to differences in their learning strategies and differing abilities to

DOI: 10.1002/smj

draw inferences. Within this diversity, we expect decision makers with more accurate mental models to make better decisions and to achieve higher performance outcomes. Of course, through good luck, vastly deficient and incorrect mental models may result in correct action in some circumstances. However, on average, we expect more accurate mental models will help direct managerial attention to the most relevant information and serve as a better guide for strategic decisions.

Managers with accurate beliefs about interdependencies between their firm, competitors, and the market have a better understanding of the market drivers, the likely effects of different actions, and the resources needed to ensure success in different strategic positions. They will better understand competitive reactions and time delays and therefore are less likely to prematurely abandon effective long-run strategies or to remain committed to failing courses of action. In summary, decision makers with more accurate mental models have a more comprehensive understanding of the fit between different strategic options and the business environment, formulate more effective strategies, and understand more fully market information and other sources of feedback compared to decision makers with less accurate mental models.

Hypothesis 1: More accurate mental models of causal relationships in the business environment result in higher performance outcomes.

As simplifications of reality, mental models will always be incomplete and inaccurate. In the complex organizational environments in which managers operate, making accurate causal inferences is often very difficult. Consequently, decision makers are unlikely to construct completely accurate mental models in even a moderately complex environment. Prior research on judgment and decision making shows that complexity—including time delays, nonlinearities, feedback effects, and stock accumulation processes—impairs the formation of accurate mental models and undermines performance (Moxnes, 1998; Paich and Sterman, 1993; Sengupta and Abdel-Hamid, 1993; Sterman, 1989a). Although greater complexity degrades the fidelity of mental models, recent simulation-based research suggests mental model accuracy becomes more important as complexity increases (Gavetti and Levinthal, 2000). Accurate mental models, the rationale goes, help managers identify promising regions of the competitive landscape. Other simulation-based strategy work suggests mental model accuracy may not be especially helpful in very simple or very complex contexts, but is instead most beneficial in moderately complex situations (Rivkin, 2001). Very simple decision environments can be effectively navigated without accurate mental models, while highly complex environments impair the development of highly accurate mental models.

Overall, prior research suggests that the benefits of mental model accuracy increase as decision environment complexity increases, but very high levels of complexity may degrade mental models so much that they are not helpful in making strategic choices. Based on these arguments, we expect the complexity of the decision environment will moderate the benefits of mental model accuracy. Decision makers with low quality, inaccurate mental models may still achieve relatively high performance outcomes in low complexity decision environments. Low complexity means there are fewer determinants to consider, fewer options, and the effects of decisions are immediate and more transparent. In these simple environments, accurate mental models may offer little competitive advantage as all managers can quickly understand feedback and adapt strategies appropriately from the limited options available. As environments become more complex, an accurate understanding of causal relationships can contribute to the quality of choices during the formulation, implementation, and evaluation of strategies. More accurate mental models help managers identify promising regions of the competitive landscape and drastically reduce the feasible strategy choices, thus affording a significant competitive advantage over managers with less accurate mental models. We expect mental model accuracy will be more important for achieving high performance outcomes in more complex decision environments.

Hypothesis 2: More accurate mental models of the causal relationships in the business environment have a greater positive effect on performance in environments that are more complex.

The discussion so far has focused on the benefits of accurate mental models of the complete business environment. However, recent simulation-based research suggests that even partial knowledge of the business environment may dramatically

DOI: 10.1002/smj

improve performance by playing an important role in seeding and constraining the process of experiential learning (Denrell *et al*., 2004; Gavetti and Levinthal, 2000). Even a small amount of knowledge may provide significant performance advantages by cutting down the search space and thereby reducing an otherwise lengthy random search process. This raises the question about whether accurate mental models of the entire business environment are required or if partial knowledge results in superior performance outcomes.

Research findings on expertise provide some guidance about the performance benefits of partial knowledge. Specifically, research shows that experts have deeper, structural-level mental representations of problems, while novices typically represent problems based on detailed, situation-specific surface characteristics (Chi, Feltovich, and Glaser, 1981). Mental representations of the deep structure of a problem domain are composed of 'chunks' of knowledge about the important key principles at work (Chase and Simon, 1973; Gentner, Loewenstein, and Thompson, 2003). Mental models of the key principles enable experts to recognize common elements and patterns across a class of problems, to quickly generate and evaluate relevant options, and to systematically outperform novices whose mental models typically focus on inconsequential details rather than the deep structure. Recent strategy work has started to explore the related issue of how experienced senior executives—with rich mental models of the deep structure or architecture of a strategic problem—often draw on solutions from past experience dealing with analogous situations (Gavetti *et al*., 2005). Based on these strands of prior research, we expect accurate mental models of key principles of the deep structure will result in superior performance outcomes, bringing us to our third hypothesis:

Hypothesis 3: More accurate mental models of key principles of the deep structure of the business environment lead to higher performance outcomes.

METHODS

We use an interactive, computer-based simulation of managing new product launch and life cycle dynamics as the experimental task in our study. We invited MBA students with no prior experience on the management simulation to participate. The 63 participants included 47 male and 16 female volunteers, with an average age of 30 and seven years of work experience. Participants were randomly assigned to either the low complexity (n = 31) or the high complexity (n = 32) group and remained in the same group throughout the experiment. All participants were paid for taking part in the experiment.

Task and procedures

The management simulation has been utilized in previous research and captures many well-established features of product life cycle management (Paich and Sterman, 1993). The core dynamic of the simulation is the process through which potential customers become aware of and choose to adopt the product. The causal relationships driving this market diffusion process are well understood (Bass, 1969; Kalish and Lilien, 1986; Mahajan, Muller, and Bass, 1995; Roberts and Urban, 1988). Customer adoption increases the installed customer base. The installed customer base generates word of mouth resulting in additional sales, but also depletion of the pool of potential customers. The customer base follows an S-shaped growth pattern where sales rise exponentially, then peak and decline to the rate of replacement purchases as the market saturates (Paich and Sterman, 1993).

Participants take on the role of chief executive officer of the firm and make quarterly decisions, such as price and production capacity expansion, with the goal to maximize cumulative profit from the sales of their product over a 40-quarter simulation. The business environment changes as a consequence of participants' decisions and includes a large number of interdependent variables with multiple feedback effects, time delays, nonlinear relationships, and stock accumulations (Paich and Sterman, 1993; Sterman, 1989a). These features of the management simulation also characterize the sort of complex environments in which senior managers typically operate while making strategic decisions.

Participants completed three phases: a learning phase, an immediate testing phase, and a delayed testing phase. The learning phase and immediate testing phases were completed in an initial laboratory session in groups of 15 to 20. Each participant was seated at a separate computer and could not see other screens. The learning phase

DOI: 10.1002/smj

included three blocks of 40 decision trials—120 decision trials in total—so participants could learn about and become familiar with the simulation. After each decision trial, participants received outcome feedback on their results for that trial plus their cumulative performance up to that point. This feedback was presented in both table and graphical format in order to control for the effects of feedback format (Atkins, Wood, and Rutgers, 2002). After each trial block of 40 quarters, the simulation was reset to the same initial values and the next trial block began. Because different decisions result in different simulated responses, the simulated outcomes could be, and were, very different from one trial block to the next.

Following the learning phase, participants were asked to complete a series of questionnaires to assess their self-efficacy and mental models of the task. After completing the questionnaires, participants proceeded to the immediate testing phase, in which they completed three more blocks of 40 decision trials on the same version of the task. Participants completed each phase at their own pace. On average, the initial experimental session took three hours. Upon completing the immediate testing phase, participants left the laboratory and were paid for their participation in the study. The delayed testing phase was completed 15 weeks later, and involved logging into the simulation from remote locations and completing three more blocks of 40 trials on the exact same version of the task. This phase was used to test the stability of the relationships proposed in all of our hypotheses.

Task complexity

Two levels of task complexity were associated with either a monopoly market or a competitive market. In the low complexity version of the task, in which there was no competitor, there were two decision variables—price and target capacity—and 19 interdependent variables in the causal structure. In the high complexity version of the task, which included causal relationships for a competitor in the market, there were three decision variables—price, target capacity, and marketing spend—and over 30 interdependent variables in the causal structure. While it is difficult to characterize any decision as inherently strategic, the set of quarterly decisions involve substantial capital, are made difficult by the complexity of the business environment, and have considerable potential to influence firm performance.

Measures

Performance

We measured performance by the cumulative profit at the end of the last decision trial for each of the nine trial blocks—three blocks completed during the learning phase, three blocks completed in the immediate testing phase, and three blocks completed in the delayed testing phase. The potential achievable cumulative profit was different in the high and low complexity task conditions; therefore we divided the raw performance scores by benchmarks for the high and low conditions. We found the performance benchmarks through a modified Powell search optimization (Powell, 1998); we fixed marketing spend at five percent of revenue throughout the simulation; we determined capacity by a perfect foresight rule in which capacity always matched demand; and we computed the single price level that optimized profits over the entire simulation. This pricing rule is very simplistic since price does not change throughout the simulation in response to changes in capacity, backlog, order demand, or any other variable in the decision environment. Therefore, the calculated cumulative profit benchmark is not a global optimum for the task, but is instead a consistently calculated benchmark enabling comparison across the two complexity groups.[1]

Mental model accuracy

We evaluated several methods for assessing the accuracy of decision makers' knowledge structures. We considered using the repertory grid technique (Reger and Huff, 1993), but this approach was not feasible given the number of variables in the management simulation. Over 900 response cells would have been necessary for the high complexity version of the task. We also considered facilitated interviews to develop individual causal loop diagrams (Huff, 1990; Sterman, 2000), but this was not practical for use in a

[1] We also analyzed alternative benchmarks including a behavioral rule previously used as a benchmark on the high complexity version of this task (Paich and Sterman, 1993). All of our results were robust to these alternative benchmarks.

large sample experiment. Although other scholars have used content analysis of written narratives to infer managerial mental models (Osborne, Stubbart, and Ramaprasad, 2001), this approach did not leverage the advantage of having direct access to decision makers in our study. We also evaluated the cognitive mapping approach in which individual decision makers draw their own cognitive maps directly (Axelrod, 1976; Hodgkinson *et al.*, 1999). After a pilot test, we ruled out this measurement approach because the participants in our study were not familiar with the cognitive mapping method. There is also evidence that actors often have poor insight into their own decision-making processes and interpretive approaches may simply capture espoused theories rather than 'theories-in-use' (Argyris and Schon, 1974: 6). Instead, we devised a knowledge test about the causal relationships in the management simulation.

The measurement of knowledge using standardized tests is a well-developed subdiscipline of education and psychology. An individual's knowledge is measured by calculating the proportion of questions answered correctly (Borgatti and Carboni, 2007). A key advantage of our laboratory experiment is that we can distinguish between correct and incorrect answers to the knowledge questions about causal relationships in the management simulation, and avoid the difficult problem of measuring mental model accuracy in field settings.

One set of questions tested participants' inferences about bivariate causal relationships between pairs of variables from the management simulation. The questions covered the exhaustive set of actual relationships in each of the complexity conditions along with several items for which no relationship existed in the decision environment. Participants answered 30 items on the relationships between variables that were common to both complexity conditions. Participants in the high complexity condition answered a further 24 items relating to the additional variables and relationships in the high complexity condition. For each question, participants drew a directed influence arrow between the two variables and indicated the polarity—sign of the slope—of the relationship if they believed a causal relationship existed (Sterman, 2000). In order to complete this first set of knowledge questions, we provided participants with a complete list of variables in the management simulation. Appendix A provides a segment of the instructions along with the first three items of this first set of questions. Figure 1 shows a diagram of the full set of causal relationships in the low complexity decision environment.[2]

A second set of questions tested participants' knowledge of the relationships between a small set of simulation variables and their ability to infer the dynamics of this set of variables. Each question presented a graph of one or two variables over time from the management simulation, and subjects chose from a multiple choice of answers for the evolution of another variable in the management simulation. To answer correctly, participants had to draw on their experience with the management simulation and their knowledge of the causal relationships between variables in order to determine how the dynamic behavior of the first variable or variables influences the dynamic behavior of another variable. This second set of questions captures whether participants' mental models accurately simulate the interaction of small sets of variables to predict subsequent events. This is an important aspect of mental models since decision makers use their mental models to predict and understand the environment by 'running' their models mentally (Norman, 1983). Appendix B provides a segment of the instructions along with one example from this set of questions. The full knowledge test is available upon request from the authors.

We scored each item on the knowledge test as correct or incorrect and each participant's mental model accuracy was the percentage of items on the knowledge test answered correctly. The possible scores range from 0 to 1, where a score of 1 indicates perfect knowledge of the tested aspects of causal structure and dynamic behavior of small sets of variables in the decision environment. It is important to note that achieving a high score on the knowledge test is no guarantee of success in the complex decision environment. Understanding bivariate causal relationships and correctly inferring the dynamics of small sets of interdependent variables supports the development of effective decision making in the complex system, but the application of this knowledge remains a difficult task.

[2] The arrows linking variables are formally defined as follows (Sterman, 2000): $x \xrightarrow{s} y \Rightarrow \frac{\partial y}{\partial x} > 0$ *and* $x \xrightarrow{o} y \Rightarrow \frac{\partial y}{\partial x} < 0$

DOI: 10.1002/smj

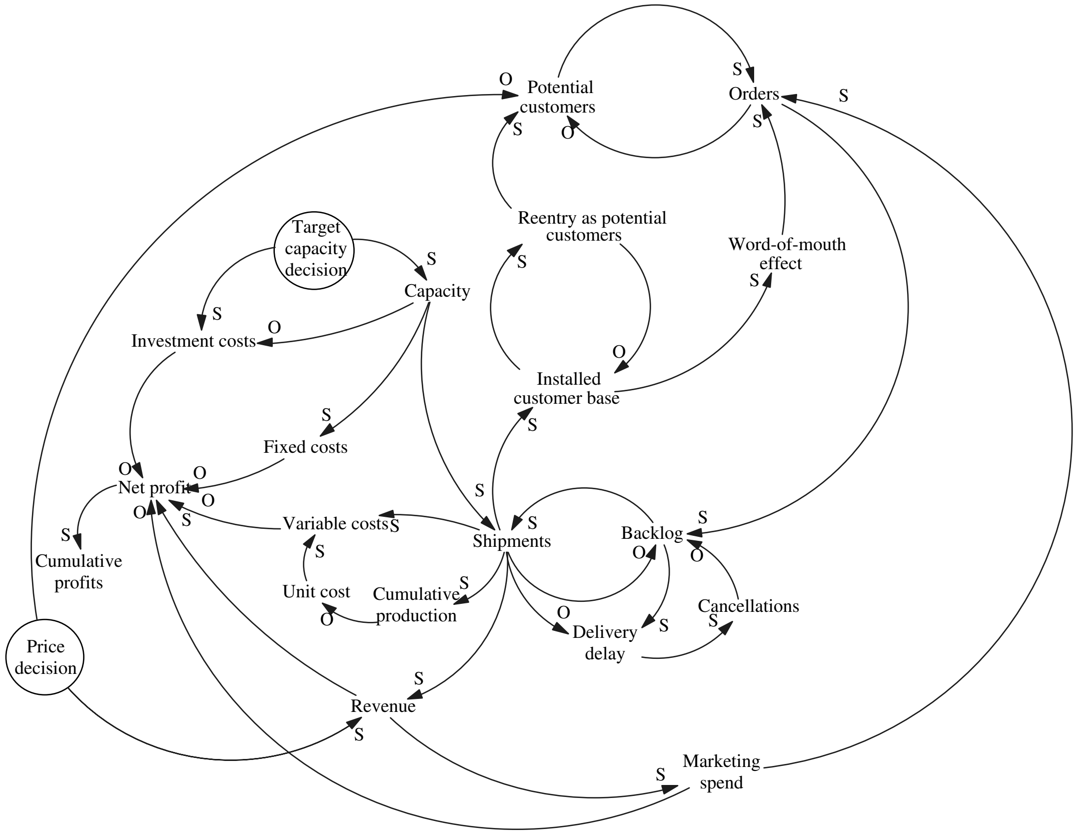


Figure 1. Causal relationships of the low complexity task

Mental model accuracy of the deep structure

We identified a subset of the causal relationships from prior research as the key principles of deep structure for the new product launch and life cycle simulation. The multidisciplinary literature on the diffusion of new products is extensive (for starting points see Mahajan, Muller, and Bass, 1990; Parker, 1994; Rogers, 1995) and shows that many new products follow roughly logistic or S-shaped growth trajectories. Much of the research has focused on identifying the causal relationships that underpin this S-shaped pattern of behavior. For example, prior research shows that an important factor driving the growth phase in new product diffusion is social contagion through word of mouth. Early purchasers tell their friends, work associates, and families about a new product, resulting in some of these potential customers buying it for themselves. Sales to potential customers increase the installed customer base and further reinforce the word-of-mouth effect. Another source of awareness and adoption identified in the literature is the level of marketing spend on advertising, promotion, public relations, and direct sales efforts. The combined effects of word of mouth and marketing spend drive the adoption rate from the pool of potential customers to the installed customer base. However, these growth processes cannot continue forever. Once the population of potential customers depletes, sales fall to the replacement level of purchases driven by the average useful lifetime of the product.

These causal relationships underpinning the market diffusion process are the well- established key principles of deep structure underlying product life cycle dynamics spanning numerous industries (Bass, 1969; Kalish and Lilien, 1986; Mahajan *et al.*, 1995; Roberts and Urban, 1988). We expect that accurate knowledge about these causal relationships will lead to a richer understanding about the dynamics of the market. In particular, decision makers with knowledge about these causal relationships, including an accurate understanding about the dynamics over time of this small set

DOI: 10.1002/smj

of interdependent variables, will realize that the customer base follows an S-shaped growth pattern where sales rise exponentially, peak, and then decline to the rate of replacement purchases as the market saturates. We expect this knowledge will be helpful in guiding decision making about capacity investments, prices, and marketing spend to avoid—or at least mitigate—the boom and bust dynamics common in new product introductions (Gary, Dosi, and Lovallo, 2008; Paich and Sterman, 1993). In contrast, decision makers who lack accurate knowledge about the market diffusion process will find it difficult to match capacity and demand over the product life cycle and performance will suffer as a result.

Eleven items from the knowledge test involving questions about inferred causal relationships and dynamic behavior of small sets of variables assess participants' knowledge of this deep structure. Appendix C provides seven example items for this measure of deep structure accuracy. The remaining four items of this measure are graphical scenario questions covering a subset of the same relationships. The graphical scenario example question in Appendix B is one of those items. Each participant's mental model accuracy of the deep structure was the percentage of these eleven items answered correctly. The possible scores range from 0 to 1, where a score of 1 indicates perfect knowledge of the tested aspects of the key principles of deep structure.

Control variables

Cognitive ability

One potentially important individual difference among decision makers in our study is cognitive ability, which has been shown to play a central role in problem solving, reasoning, and learning (Anderson, 1990). We used participants' scores on the Graduate Management Aptitude Test (GMAT) as a proxy for general cognitive ability. The GMAT is widely used to assess general cognitive ability of applicants to MBA programs around the world. GMAT scores are commonly used in the admissions process as a selection criterion and are thought to reflect the achievement and learning potential of applicants in the domain of management.

Perceived self-efficacy

Self-efficacy is an established motivational predictor of performance on complex tasks and the constituent processes—such as search, information processing and memory processes—that can affect learning (Bandura, 1997). Also, complexity levels have been shown to influence the motivational reactions to tasks (Wood, Bandura, and Bailey, 1990). Therefore, we incorporated self-efficacy to control for differences in performance attributable to motivational differences. We measured perceived self-efficacy with a 10-item scale, available from the authors, covering a broad range of activities involved in managing the simulated firm. The format followed the approach recommended by Bandura (1997), which has been validated in numerous empirical studies. For each item, participants first recorded whether or not they understood what was required to manage the activity—yes or no—and then recorded their confidence in their capabilities on a 10-point scale where 1 = 'very low confidence' and 10 = 'very high confidence.' We computed the perceived self-efficacy score by taking the mean confidence level across all 10 items.

Mental model complexity

A number of prior studies have used mental model complexity as an indication of the richness and accuracy of managers' mental models. The basic idea is that more complex knowledge structures are necessary for coping with the multidimensional challenges of complex organizational realities, and enable managers to respond appropriately in complex environments. The complexity of top managers' mental models has also been positively linked to competitive success (McNamara, Luce, and Tompson, 2002). Therefore, we included mental model complexity as a control variable in order to distinguish between the effects of complex mental models and accurate mental models.

We measured the complexity of decision makers' mental models by counting the number of inferred causal relationships in the set of knowledge questions assessing beliefs about bivariate causal relationships. Reported perceived relationships were included in the count whether these causal relationships were correct or not. The potential number of perceived bivariate relationships was different in the high and low complexity

DOI: 10.1002/smj

task conditions, and therefore we divided the raw counts by the correct number of causal relationships in each condition. The result assesses the complexity of decision makers' mental models relative to the complexity of the perfectly correct mental model. Possible scores range from 0 to values greater than 1, where a score less than 1 indicates less complexity than in the correct mental model and a score greater than 1 indicates more complexity than the correct mental model due to inaccurate beliefs.

Data analyses

We tested the relationships proposed in Hypotheses 1–3 by estimating both ordinary least squares (OLS) regressions and linear mixed models with repeated measures. In the OLS models, the dependent variable was performance at the end of either trial block 6—the final trial block of the immediate testing phase—or trial block 9—the final trial block of the delayed testing phase. In the linear mixed models with repeated measures, performance for trial blocks 4–9 in the immediate and delayed testing phases were all dependent variables, increasing the statistical power and reducing bias in the estimates. Task complexity was a between-subjects fixed effect. We specified a first-order, autoregressive correlation structure for the repeated measures of performance across trial blocks. Trial block was also included as a fixed effect. In addition, a random intercept was included for each participant. Linear mixed models provide the best linear unbiased estimates for unbalanced, correlated repeated measures data (Verbeke and Molenberghs, 2000).

RESULTS

Table 1 provides the correlations, means, and standard deviations for all study variables. Task complexity was coded such that 0 = low complexity and 1 = high complexity. Task complexity is negatively correlated with mental model accuracy and performance across all trial blocks. Mental model accuracy is positively correlated with performance across all trial blocks. In addition, mental model accuracy ranges from 0.32–0.81 with mean 0.56 and standard deviation 0.11, demonstrating substantial variance. Decision makers in the low complexity condition have significantly more accurate mental models [$t(61) = 2.73$, $p < 0.01$] than the high complexity group. As expected, complexity impairs the development of accurate mental models.

Figure **2** illustrates mean performance and 95 percent confidence intervals across all nine trial blocks for the high and low complexity groups. The learning phase includes trial blocks 1–3, the immediate testing phase includes trial blocks 4–6, and the delayed testing phase includes trial blocks 7–9. Performance in both complexity conditions improves considerably from trial block 1 to trial block 3, but plateaus relatively quickly in the experiment. Performance falls slightly in the delayed testing phase but the difference is not statistically significant. The 95 percent confidence intervals show there is considerable variation in performance across decision makers in the same version of the management simulation task.

Tests of hypotheses

Models 1–3 of Table 2 test the impact of mental model accuracy of the business environment on performance proposed in Hypothesis 1. Model 1 provides the OLS estimates using performance on trial block 6, the last immediate testing phase trial block, as the dependent variable. In support of Hypothesis 1, mental model accuracy is a significant predictor of performance ($b = 1.039$, $p < 0.05$) after controlling for task complexity, general cognitive ability, and self-efficacy. To help interpret the effect size, the standardized coefficient for mental model accuracy is equal to 0.30. If we increase mental model accuracy by one standard deviation from its mean—assuming all other variables remain at their mean levels—performance increases by 22 percent. Task complexity has a significant and negative main effect on performance ($b = -0.434$, $p < 0.001$), indicating that participants in the high complexity condition achieved significantly lower performance outcomes than participants in the low complexity group. General cognitive ability, self-efficacy, and mental model complexity were not significant predictors of performance.

Model 2 provides the OLS estimates using performance on trial block 9, the last delayed testing phase trial block, as the dependent variable. The results are the same as in Model 1. In fact, the effects of mental model accuracy on performance ($b = 1.668$, $p < 0.05$) are even stronger in

Table 1. Correlations, means and standard deviations for study variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. GMAT	1														
2. Task complexity	0.02	1													
3. Performance trial block 1	0.17	−0.50**	1												
4. Performance trial block 2	0.10	−0.58**	0.43**	1											
5. Performance trial block 3	0.03	−0.71**	0.45**	0.74**	1										
6. Performance trial block 4	0.17	−0.65**	0.47**	0.72**	0.87**	1									
7. Performance trial block 5	0.13	−0.63**	0.50**	0.74**	0.85**	0.92**	1								
8. Performance trial block 6	0.08	−0.66**	0.51**	0.75**	0.83**	0.87**	0.90**	1							
9. Performance trial block 7	−0.02	−0.68**	0.42**	0.55**	0.58**	0.63**	0.61**	.687**	1						
10. Performance trial block 8	0.13	−0.62**	0.39*	0.58**	0.66**	0.70**	0.66**	.737**	0.78**	1					
11. Performance trial block 9	0.14	−0.61**	0.46**	0.54**	0.59**	0.62**	0.63**	.709**	0.85**	0.79**	1				
12. Self-efficacy	0.14	−0.33**	0.27*	0.28*	0.25*	0.29*	0.27*	.281*	0.35*	0.40**	0.33*	1			
13. Mental model accuracy	0.37**	−0.33**	0.31*	0.43**	0.38**	0.37**	0.39**	.442**	0.37*	0.48**	0.53**	0.23	1		
14. Mental model complexity	0.11	−0.28*	0.18	0.23	0.15	0.08	0.13	.194	0.28	0.26	0.37*	0.30*	0.41**	1	
15. Deep structure accuracy	0.40**	−0.27*	0.40*	0.25*	0.26*	0.27*	0.30*	.387**	0.36*	0.56**	0.50**	0.28*	0.77**	0.31*	1
Total															
Mean	642.22	0.51	0.04	0.32	0.43	0.46	0.51	0.51	0.43	0.49	0.47	5.66	0.56	0.84	0.39
Std. deviation	54.30	0.50	0.78	0.43	0.38	0.37	0.36	0.37	0.37	0.43	0.46	1.28	0.11	0.19	0.14
N	63	63	63	63	63	63	62	62	43	42	43	63	63	63	63
Low complexity															
Mean	641.19		0.43	0.57	0.70	0.71	0.73	0.75	0.65	0.71	0.71	6.08	0.60	0.89	0.43
Std. deviation	56.72		0.34	0.38	0.32	0.32	0.34	0.33	0.32	0.30	0.33	1.23	0.10	0.14	0.14
N	31		31	31	31	31	31	31	24	24	24	31	31	31	31
High complexity															
Mean	643.22		−0.34	0.08	0.17	0.23	0.29	0.26	0.15	0.19	0.16	5.25	0.53	0.79	0.36
Std. deviation	52.73		0.89	0.33	0.21	0.24	0.21	0.21	0.20	0.38	0.41	1.20	0.10	0.21	0.14
N	32		32	32	32	32	31	31	19	18	19	32	32	32	32

** $p < 0.01$, two-tailed.
* $p < 0.05$, two-tailed.

DOI: 10.1002/smj

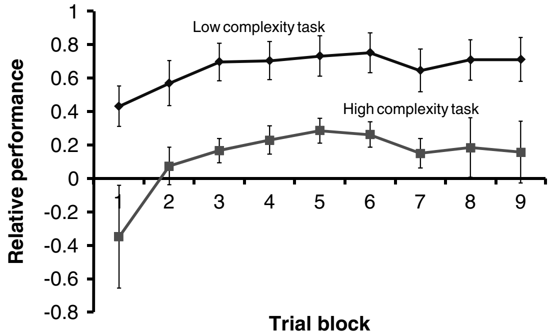


Figure 2. Mean performance relative to benchmark and 95% confidence intervals for low and high complexity groups across all nine trial blocks

the delayed testing phase than in the immediate testing phase. The standardized coefficient for mental model accuracy is 0.41, and increasing mental model accuracy by one standard deviation increases performance by 40 percent. This indicates decision makers' mental models of the management simulation remained stable 15 weeks after the initial laboratory session and continued to impact performance. Model 3 provides linear mixed model estimates using repeated measures for performance on trial blocks 4–9, all of the immediate and delayed testing phases, increasing the number of observations to 315. Again, the results are the same as in Models 1 and 2 with a significant, positive relationship between mental

Table 2. Impact of mental model accuracy of the complete business environment on performance

Variables	Model 1[a]	Model 2[b]	Model 3[c]	Model 4[d]
Intercept	0.321	−0.091	0.168	0.098
	(0.437)	(0.624)	(0.371)	(0.405)
Task complexity	−0.434***	−0.432**	−0.438***	−0.439***
	(0.078)	(0.128)	(0.067)	(0.067)
Self-efficacy	0.016	0.011	0.020	0.020
	(0.030)	(0.045)	(0.025)	(0.025)
GMAT (cognitive ability)	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Mental model complexity	−0.263	−0.038	−0.269	−0.286
	(0.216)	(0.364)	(0.185)	(0.190)
Mental model accuracy	1.039*	1.668*	0.988**	1.123*
	(0.392)	(0.619)	(0.335)	(0.456)
MentalModAcc X				−0.263
Task complexity				(0.593)
Adjusted R^2	0.470	0.434		
F	11.81	7.442		
Observations	61	42	315	315
Number of parameters	6	6	14	15
−2 restricted log likelihood			−7.041	−8.023
Akaike's inf. criterion (AIC)			−1.041	−2.023
Schwarz's Bayesian (BIC)			10.111	9.118

Notes:
Unstandardized coefficients with standard errors in parentheses
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
[a] Dependent variable is performance on 6th trial block and the OLS model is:
$\text{Perf}_6 = \text{Intercept} + B_1\text{TaskComplexity} + B_2\text{SelfEff} + B_3\text{GMAT} + B_4\text{MentalModComplex} + B_5\text{MentalModAcc} + \varepsilon$
[b] Dependent variable is performance on 9th trial block and the OLS model is:
$\text{Perf}_9 = \text{Intercept} + B_1\text{TaskComplexity} + B_2\text{SelfEff} + B_3\text{GMAT} + B_4\text{MentalModComplex} + B_5\text{MentalModAcc} + \varepsilon$
[c] Dependent variable is performance on trial blocks 4–9 (repeated measures) and the linear mixed model is:
$\text{Perf}_{it} = \beta_1 + \beta_2\text{TaskComplexity}_i + \beta_3\text{SelfEff}_i + \beta_4\text{GMAT}_i + \beta_5\text{MentalModComplex}_i + \beta_6\text{MentalModAcc}_i + \beta_7\text{TrialBlk}_{i4} + \beta_8\,\text{TrialBlk}_{i5} + \beta_9\text{TrialBlk}_{i6} + \beta_{10}\text{TrialBlk}_{i7} + \beta_{11}\text{TrialBlk}_{i8} + b_1 + \varepsilon_{it}$
where $\beta_1 - \beta_{11}$ are the fixed-coefficients (including the intercept term β_1), b_1 is the random-effect intercept capturing the variance among subject i intercepts, and ε_{it} is the error for observation t of subject i and is modeled using a first-order autoregressive structure to account for the correlation within individuals. Two parameters are estimated for the first-order autoregressive structure $\varepsilon_{it} = \varphi\varepsilon_{i,t-1} + \nu_t$ where $\nu_t \sim \text{NID}(0, \sigma_\nu^2)$ and the autocorrelation between two errors one time-period apart is $\rho(1) = \varphi$.
[d] Dependent variable is performance on trial blocks 4–9 (repeated measures) and the linear mixed model is:
$\text{Perf}_{it} = \beta_1 + \beta_2\text{TaskComplexity}_i + \beta_3\text{SelfEff}_i + \beta_4\text{GMAT}_i + \beta_5\text{MentalModComplex}_i + \beta_6\text{MentalModAcc}_i + \beta_7\text{TrialBlk}_{i4} + \beta_8\,\text{TrialBlk}_{i5} + \beta_9\text{TrialBlk}_{i6} + \beta_{10}\text{TrialBlk}_{i7} + \beta_{11}\text{TrialBlk}_{i8} + \beta_{12}\text{MentalModAcc X TaskComplexity} + b_1 + \varepsilon_{it}$

Table 3. Impact of mental model accuracy of the deep structure on performance

Variables	Model 1[a]	Model 2[b]	Model 3[c]
Intercept	0.480	0.428	0.305
	(0.440)	(0.624)	(0.377)
Task complexity	−0.442***	−0.471***	−0.446***
	(0.076)	(0.121)	(0.066)
Self-efficacy	0.004	−0.005	0.008
	(0.030)	(0.044)	(0.026)
GMAT (cognitive ability)	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Deep structure accuracy	0.596*	1.178**	0.555*
	(0.286)	(0.417)	(0.245)
Adjusted R^2	0.454	0.443	
F	13.704***	9.36***	
Observations	61	42	315
Number of parameters	5	5	13
−2 restricted log likelihood			−4.479
Akaike's inf. criterion (AIC)			1.521
Schwarz's Bayesian (BIC)			12.682

Notes:
Unstandardized coefficients with standard errors in parentheses
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
[a] Dependent variable is performance on 6th trial block and the OLS model is:
$\text{Perf}_6 = \text{Intercept} + B_1\text{TaskComplexity} + B_2\text{SelfEff} + B_3\text{GMAT} + B_4\text{DeepStrucAcc} + \varepsilon$
[b] Dependent variable is performance on 9th trial block and the OLS model is:
$\text{Perf}_9 = \text{Intercept} + B_1\text{TaskComplexity} + B_2\text{SelfEff} + B_3\text{GMAT} + B_4\text{DeepStrucAcc} + \varepsilon$
[c] Dependent variable is performance on trial blocks 4–9 (repeated measures) and the linear mixed model is:
$\text{Perf}_{it} = \beta_1 + \beta_2\text{TaskComplexity}_i + \beta_3\text{SelfEff}_i + \beta_4\text{GMAT}_i + \beta_5\text{DeepStrucAcc}_i + \beta_6\text{TrialBlk}_{i4} + \beta_7\text{TrialBlk}_{i5} + \beta_8\text{TrialBlk}_{i6} + \beta_9\text{ TrialBlk}_{i7} + \beta_{10}\text{TrialBlk}_{i8} + b_1 + \varepsilon_{it}$

model accuracy and performance ($b = 0.988$, $p < 0.01$) and a negative main effect of task complexity on performance ($b = -0.438$, $p < 0.001$).[3]

Model 4 includes the interaction of task complexity and mental model accuracy to test Hypothesis 2. The interaction term is not significant, indicating that more accurate mental models do not have a greater positive effect on performance in environments that are more complex. The data do not support Hypothesis 2. Overall, the results of Models 1–4 of **Table 2** support Hypothesis 1 and provide empirical evidence that more accurate mental models of the business environment lead to higher performance outcomes.

Models 1–3 of Table 3 test the impact of accurate mental models of the deep structure on performance proposed in Hypothesis 3. Model 1 provides the OLS regression estimates using performance on trial block 6, the last immediate testing phase trial block, as the dependent variable. Deep structure accuracy has a significant positive impact on performance ($b = 0.596$, $p < 0.05$). Decision makers do not need an accurate mental model of the complete business environment, but rather accurate mental models of key principles of the deep structure. To help interpret the effect size, the standardized coefficient for deep structure accuracy is equal to 0.23. If we increase deep structure accuracy by one standard deviation from its mean—assuming all other variables remain at their mean levels—performance increases by 17 percent. As established previously, task complexity has a significant negative effect on performance ($b = -0.442$, $p < 0.001$). General cognitive ability and self-efficacy were not significant predictors of performance. Model 2 provides the OLS estimates using performance on trial block 9, the last delayed testing phase trial block, as the dependent variable.

[3] To simplify the presentation of results, we do not show the fixed effects associated with each trial block and the three variance-covariance components for the random-effect intercept and the autoregressive structure of the repeated measures. Trial block is not significant in any of our analyses due to the performance plateau that occurs after the learning phase (refer back to Figure 3). The repeated component of all models is significant, indicating that residual errors are correlated by trial block. In addition, the random subject intercept is also significant in all models, indicating that performance varies between individuals.

The results are the same as in Model 1 and, as in the previous analysis with mental model accuracy, the effects of deep structure accuracy on performance ($b = 1.178$, $p < 0.01$) are even stronger in the delayed testing phase than in the immediate testing phase. The standardized coefficient for deep structure accuracy is equal to 0.39, and increasing deep structure accuracy by one standard deviation increases performance by 38 percent. Model 3 provides linear mixed model estimates using repeated measures for performance across trial blocks 4–9. The results are the same as in Models 1 and 2 with a significant and positive impact of deep structure accuracy on performance ($b = 0.555$, $p < 0.05$) and a negative effect of task complexity on performance ($b = -0.446$, $p < 0.001$).

To assess the importance of deep structure knowledge relative to partial knowledge about any subset of the competitive environment, we tested whether the improvement in R square when we add deep structure accuracy to the models is significantly better than the change in R square obtained when randomly chosen partial knowledge variables are added to the model instead.[4] The unadjusted R square of Model 1 in Table 3 with task complexity, self-efficacy, and GMAT included as independent variables and performance on trial block 6 as the dependent variable is 0.45. When deep structure accuracy is added to the model, unadjusted R square increases to 0.49. This change in R square of 0.04 is significant ($p < 0.05$).

Next, we generated 1,000 random samples of 11 knowledge test items—out of 69 items on the high complexity condition and 42 items in the low complexity condition—to compute 1,000 partial knowledge variables. We used 11 items to measure deep structure accuracy, so we kept this consistent when computing random partial knowledge variables. We ran Model 1 regressions separately for all 1,000 partial knowledge variables and computed the change in R square for each partial knowledge variable. The mean R square change across the 1,000 partial knowledge variables was 0.025 ($N = 1{,}000$; std dev $= 0.022$; std error $= 0.00068$) with a 95 percent confidence interval of [0.024–0.027]. The change in R square for deep structure accuracy, 0.04, is significantly different from the mean change in R square for the 1,000 partial knowledge variables ($t = -19.98$, $p < 0.001$).

We repeated this analysis again for Model 2 in Table 3. The unadjusted R square of Model 2 with intercept, task complexity, self-efficacy, and GMAT included as independent variables and performance on trial block 9 as the dependent variable is 0.39. When deep structure accuracy is added to the model, unadjusted R Square increases to 0.496. This change in R square of 0.106 is significant ($p < 0.01$). In addition, this change in R square for deep structure accuracy is significantly better ($t = -38.40$, $p < 0.001$) than the mean change in R square across the 1,000 partial knowledge variables. Overall, these results show that accurate knowledge about key principles of the deep structure leads to superior performance.

Decision rules and strategies

To further investigate the mechanisms linking mental models and performance, we performed supplementary analyses of participants' decisions. In the face of complexity, decision makers adopt satisficing rules of thumb and heuristics that are intended to be consistent with their simplified mental models of the business environment (Cyert and March, 1992; Levitt and March, 1988; March and Simon, 1958; Simon, 1991). Mental models encompass beliefs about what information is most relevant in a given situation and how much weight to give to different pieces of information when making decisions. Decisions resulting in favorable outcomes are repeated when the same situation is encountered again and, in due course, this leads to the development of rules of thumb for making decisions that managers have seen in the past (Cyert and March, 1992; Levitt and March, 1988). Over time, these decision rules are likely to be executed more and more automatically without high levels of cognitive effort or conscious processing (Argyris and Schon, 1974).

Research shows that linear models of decision making often provide good, higher level representations of underlying processes (Camerer, 1981; Cyert and March, 1992; Einhorn, Kleinmuntz, and Kleinmuntz, 1979; Levitt and March, 1988). Supported by post experiment interviews, analysis of participants' experimental logs, and the decision rules identified in previous research for this new product launch experimental task (Paich and Sterman, 1993), we identified linear decision rules for pricing and capacity investment decisions for each participant.

---

[4] We thank an anonymous reviewer for this helpful suggestion.

Participants' capacity investment decisions involved estimating future demand by extrapolating current demand using the recent growth rate, and then making adjustments to balance capacity with expected future demand. Capacity adjustments do not happen instantaneously in most organizational settings or in our management simulation. Instead, decision makers set a target capacity level and, after a time delay, the actual level of production capacity approaches this target value. This time delay in combination with the requirement for accurate expectations with respect to future demand, makes the capacity investment decision dynamically complex (Sterman *et al.*, 2007; Zajac and Bazerman, 1991). Equation 1 shows the form in which participants' capacity decision rules were estimated; where C^* is target capacity, D is actual demand, g is fractional demand growth over the last two quarters, B is backlog, C is capacity, the subscript t is time, and the subscript $t-1$ is the current time lagged by one period. We estimated parameters for the intercept c and the information weights a_0, a_1, and a_2.

$$\log(C_t^*) = c + a_0 \log(D_{t-1}) + a_1 \log(1 + g_{t-1}) + a_2 \log(B_t/C_t) + \varepsilon_1 \quad (1)$$

Participants' pricing decisions involved a markup from unit variable cost, with margin over cost driven by the ratio of demand to capacity. This markup pricing rule is consistent with behavioral pricing rules documented in organizations from a wide range of competitive environments (Cyert and March, 1992). Equation 2 shows the form in which we estimated this pricing decision rule; where P is price, UVC is unit variable cost, B is backlog, C is capacity, the subscript t is time, and the subscript $t-1$ is the current time lagged by one period. We estimated parameters for the intercept b_0 and the information weights b_1 and b_2.

$$\log(P_t) = b_0 + b_1 \log(UVC_{t-1}) + b_2 \log(B_t/C_t) + \varepsilon_2 \quad (2)$$

The information weights for the capacity and pricing decision rules were estimated separately for each trial block for each participant using Prais-Winsten regressions to correct for first-order autocorrelation (Camerer, 1981; Einhorn *et al.*, 1979). These decision rules capture the majority of the variance in participants' decisions in both complexity conditions. The mean adjusted R square values for the high and low complexity conditions are 0.75 and 0.85 respectively for the target capacity rule, and 0.97 and 0.92 for the price rule. For the capacity and pricing decision rules, we also computed the optimal information weights maximizing cumulative profit.[5] These should in no way be construed as the global optimal decision rules for the management simulation since the rules only incorporate a handful of information cues in accordance with the information processing constraints of boundedly rational decision makers. We used the optimal information weights for these rules to calculate how far participants' information weights deviated from the optimal values.[6]

We estimated linear mixed models with repeated measures to investigate the relationships between mental models and decision rules using deviation from the optimal information weights across trial blocks 4–9 as the dependent variable. Larger deviations indicate less effective decision rules and Models 1–3 of **Table 4** show the results.[7] Model 1 shows that mental model accuracy of the business environment has a significant impact ($b = -3.40$, $p < 0.001$), with more accurate mental models reducing the deviation from optimal information weights. Task complexity also has a significant impact ($b = 2.64$, $p < 0.001$) indicating participants' decision rules in the high complexity condition deviate more from the optimal information weights than participants in the low complexity group. Model 2 shows that more accurate mental models of the deep structure result in more effective decision rules with significantly smaller deviations from the optimally computed information weights ($b = -2.14$, $p < 0.01$). Overall, these results provide evidence for a positive relationship between mental models and effective decision heuristics. Establishing the link between mental model accuracy and decision rules highlights one more mechanism connecting mental models and performance variation.

[5] The optimal information weights were computed using the Powell algorithm with random multiple starts over more than 10 million simulations.

[6] We adjusted the deviations by a weighting factor to account for the sensitivity of performance to each information cue, and then the absolute differences summed across all information cues in both decision rules.

[7] Twelve cases—out of 315 total repeated measures cases—were identified as extreme outliers across multiple information weights and removed for the analysis.

DOI: 10.1002/smj

Table 4. Impact of mental model accuracy on deviation from optimal information weights

Variables	Model 1[a]	Model 2[b]
Intercept	3.170**	2.182*
	(1.004)	(1.068)
Task complexity	2.640***	2.736***
	(0.190)	(0.189)
Self-efficacy	−0.062	−0.041
	(0.068)	(0.072)
GMAT (cognitive ability)	0.003	0.003
	(0.002)	(0.002)
Mental model accuracy	−3.398***	
	(0.883)	
Deep structure accuracy		−2.140**
		(0.702)
Observations	297	297
Number of parameters	13	13
−2 restricted log likelihood	767.896	772.923
Akaike's inf. criterion (AIC)	773.896	778.923
Schwarz's Bayesian (BIC)	784.874	789.901

Notes:
Unstandardized coefficients with standard errors in parentheses
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
Deviation from optimal information weights on trial blocks 4–9 is the dependent variable
[a] $\text{Dev\_from\_Opt\_Weights}_{it} = \beta_1 + \beta_2\text{TaskComplexity}_i + \beta_3\ \text{SelfEff}_i + \beta_4\text{GMAT}_i + \beta_5\text{MentalModAcc}_i + \beta_6\text{TrialBlk}_{i4} + \beta_7\ \text{TrialBlk}_{i5} + \beta_8\text{TrialBlk}_{i6} + \beta_9\text{TrialBlk}_{i7} + \beta_{10}\text{TrialBlk}_{i8} + b_1 + \varepsilon_{it}$
[b] $\text{Dev\_from\_Opt\_Weights}_{it} = \beta_1 + \beta_2\text{TaskComplexity}_i + \beta_3\ \text{SelfEff}_i + \beta_4\text{GMAT}_i + \beta_5\text{DeepStrucAcc}_i + \beta_6\text{TrialBlk}_{i4} + \beta_7\ \text{TrialBlk}_{i5} + \beta_8\text{TrialBlk}_{i6} + \beta_9\text{TrialBlk}_{i7} + \beta_{10}\text{TrialBlk}_{i8} + b_1 + \varepsilon_{it}$

Further analysis of participants' pricing and capacity decision rules shows rapid stabilization of the information weights for both rules. The evolution of decision rules were tested using ANOVA contrasts comparing the information weights between trial blocks with the data pooled across participants and analyzed separately for each level of complexity. For the capacity investment decision rules, there are some significant differences between information weights on the first four trial blocks. However, there are no significant differences between information weights in all subsequent trial blocks of the immediate testing phase. In the pricing decision rule, there are no significant differences between information weights throughout all trial blocks of the learning and immediate testing phases. These results provide evidence that participants formed decision rules rapidly and largely stabilized the information weights for these rules by the end of trial block 4 with little adjustment thereafter. This speedy stabilization of the decision rules helps explain why average performance plateaus so rapidly.

Our analysis of decision rules shows a great deal of variation in participants' information weights. To the extent that there are distinctive patterns of decision rules, this could be evidence of different high-level policies or strategies. Recent strategy research suggests different configurations of specific choice and decision sets lie below the surface of higher-level policies and overarching strategies (Gavetti *et al*., 2005). Managers and firms vary in terms of the overall strategies they adopt. For example, a firm that adopts a pricing rule to capture market share by dropping price as unit cost decreases over time (e.g., due to learning curve effects) and a capacity investment rule that rapidly expands capacity to fulfill demand could be characterized as adopting a 'get-big-fast' cost leadership strategy (Sterman *et al*., 2007). Different patterns of decision rules could similarly represent other generic strategies such as a premium price, niche strategy, as well as many other mixed strategies. These strategies may be the result of either rational *ex ante* planning or emergent behavior. Identifying different strategies by examining the observed patterns in decision rules is necessarily exploratory, but enables us to investigate heterogeneity in strategies and the relationships between mental models and strategies.

We used two-stage cluster analysis of the information weights to explore patterns in the decision rules. The first stage involved hierarchical analysis to identify outliers and centroid means, followed by k-means nonhierarchical analysis to identify distinctive strategies (Ketchen and Shook, 1996).[8] As shown in Table 5, this analysis identified five distinct strategies for the low complexity task condition and four distinct strategies for the high complexity task condition. These strategies capture the range of observed patterns in the pricing and capacity investment decision rules. For example, the tenacious build and hold strategy in the low complexity task combined building capacity to an initial forecast—as indicated by the large intercept for capacity investment—along with reducing

[8] We ran analyses separately for each task complexity condition and the results were robust to using different distance algorithms for identifying clusters.

Table 5. Distinct strategies identified in the high and low complexity task conditions

Strategies	Description	N[a]	Perf[b]	Mental model acc[c]	Capacity invest. decision rule[d]				Pricing decision rule[e]		
					Intercept	Orders	Growth	Backlog/capacity	Intercept	Cost	Backlog/capacity
Low complexity strategies											
[1] Tenacious build and hold	Build capacity to initial forecast and maintain position while reducing price	59	0.74	0.60	12.78	0.10	0.05	0.27	2.34	0.57	0.05
[2] Slow going	Slow and cautious capacity investment with high price	47	0.72	0.62	11.87	0.09	0.04	0.18	7.18	−0.66	0.02
[3] Aggressive	Responsive capacity adjusted to market demand while maintaining fixed price	28	0.92	0.64	7.28	0.48	0.38	0.53	4.51	0.02	0.02
[4] Hold your horses	Capacity investment lags demand with aggressive price cutting	40	0.74	0.56	5.04	0.65	−0.13	−0.03	2.19	0.60	0.03
[5] Premium price	Charge price premium and avoid excess capacity by following demand	68	0.55	0.60	6.46	0.51	−0.10	0.01	5.83	−0.28	0.05
High complexity strategies											
[1] Cautious niche	Raise margin when excess demand and cautious capacity expansion	62	0.16	0.50	8.69	0.33	0.04	0.08	−1.45	1.47	0.05
[2] Build to initial forecast	Build capacity to initial forecast and maintain constant margin	77	0.30	0.53	11.72	0.14	0.24	0.42	0.74	0.88	0.01
[3] Show me	Invest in capacity only after seeing demand and drop prices as unit costs fall	76	0.02	0.52	2.35	0.79	0.02	−0.06	0.35	0.97	−0.01
[4] Rapid response	Aggressive capacity adjusted to match demand and drop prices as unit costs fall	16	0.49	0.62	10.13	0.23	1.22	1.62	0.73	0.88	0.00

Notes:
[a] Number of decision makers adopting each strategy over trial blocks 1–9.
[b] Mean performance across trial blocks 4–9 for each strategy.
[c] Mean mental model accuracy across trial blocks 4–9 for each strategy.
[d] Mean information weights (cluster centroids) for the capacity investment decision rule for each strategy over trial blocks 1–9.
[e] Mean information weights (cluster centroids) for the pricing decision rule for each strategy over trial blocks 1–9.

DOI: 10.1002/smj

price as unit costs fall, as indicated by a relatively large cue weight for unit cost. Figure 3 illustrates the different patterns of capacity investment decisions for the four distinct strategies in the high complexity condition. Similarly, Figure 4 illustrates the different patterns of pricing decisions associated with the five distinct strategies in the low complexity decision environment.

ANOVA shows there are significant differences in both mental model accuracy ($F = 5.372$, $p < 0.01$) and performance ($F = 14.745$, $p < 0.001$) between the four distinctive strategies in the high complexity decision environment. There are also significant differences in performance ($F = 3.064$, $p < 0.05$) and marginally significant differences in mental model accuracy ($F = 2.300$, $p = 0.06$) between the five distinctive strategies in the low complexity decision environment. Establishing these differences shows an additional mechanism connecting mental models and performance variation. Specifically, the accuracy of decision makers' mental models influences the strategies they adopt and there are significant performance differences between the different strategies.

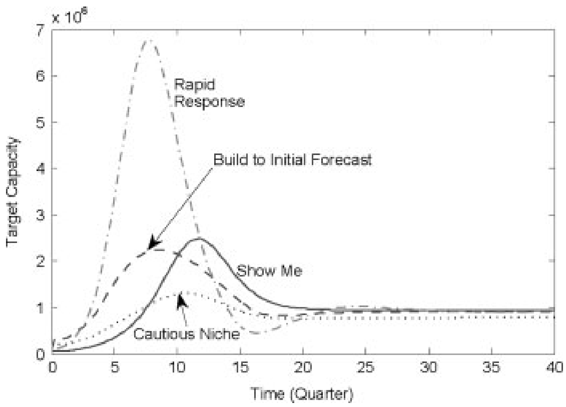


Figure 3. Different patterns of target capacity decisions for the four high complexity strategies

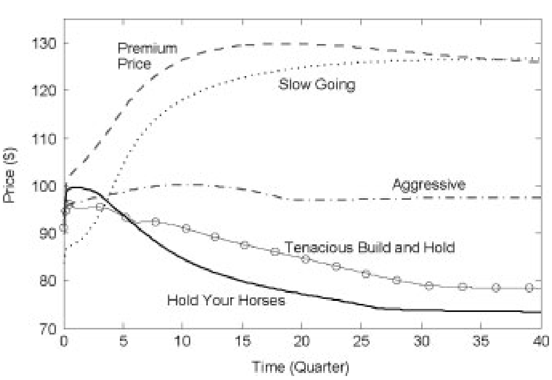


Figure 4. Different patterns of pricing decisions for the five strategies in the low complexity task

We also ran the complete set of pairwise tests of the differences in mental model accuracy and performance across the various strategies. The results show that decision makers with the most accurate mental models adopt the best strategies and achieve superior performance under both complexity conditions. However, at lower levels of mental model accuracy, the connection between mental model accuracy, the strategies adopted, and performance outcomes achieved are not as straightforward. These findings suggest there may be threshold effects relating mental models to the selection of higher level strategies. It is important to highlight that we are not suggesting that the highest performing strategies in the simulation are the optimal strategies for firms to adopt when launching new products and managing the life cycle. Instead, these results demonstrate there are links between decision makers' mental models and the different strategies they adopt, and connect heterogeneity in mental model accuracy, decision rules, and strategies to variation in performance outcomes.

DISCUSSION

Our results provide empirical evidence for the links between mental models and performance outcomes and help explain why some managers and not others adopt strategies that are ultimately associated with competitive success. We found substantial variation in the accuracy of decision makers' mental models and in performance. While it is certainly true that perfect mental models are not necessary to reach high performance outcomes (Sutcliffe, 1994; Weick, 1990), our findings show that decision makers with more accurate mental models of the causal relationships in the business environment achieve higher performance outcomes. Further, this relationship not only remained stable but also grew stronger between the immediate and delayed testing phases, providing evidence that decision makers' mental models of the experimental task were not ephemeral.

Our results are consistent with the limited prior empirical research findings about the importance of accurate mental models (Barr *et al.*, 1992;

Bourgeois, 1985), and extend prior work by providing systematic evidence connecting differences in mental models of causal relationships with performance heterogeneity. Our findings also help address an important challenge facing the strategy field about whether more accurate mental models enable managers *ex ante* to identify and interpret signals from their business environment that lead to superior strategic choices and performance outcomes (Cockburn *et al*., 2000). In our experimental study, variation in mental model accuracy is a key source of performance heterogeneity.

Our findings also show that managers do not need accurate mental models of the entire business environment. Accurate mental models about the key principles of the business environment lead to superior decision rules and performance outcomes. These results support recent theoretical work in strategy positing the benefits of partial knowledge (Denrell *et al*., 2004; Gavetti and Levinthal, 2000), and extend this work by providing evidence that all partial knowledge is not equally valuable. The benefits of partial knowledge about the key principles far outweigh the benefits of other partial knowledge. Our findings are also consistent with prior research showing that experts with richer cognitive representations of the deep structure of problems outperform novices who typically focus on superficial features of problems (Chi *et al*., 1981; Gentner *et al*., 2003). An important implication is that managers do not need to develop perfect and complete mental models of complex business environments, but should instead focus on identifying and understanding the key principles.

We also find considerable variation in decision rules and that more accurate mental models and deep structure accuracy lead to more effective decision rules. These findings extend research examining the detrimental mean effects of decision biases and heuristics (e.g., Kahneman and Tversky, 2000; Sterman, 1989b; Zajac and Bazerman, 1991). Specifically, our results provide evidence of heterogeneity in decision rules and connect these differences to mental model accuracy. We also find a number of distinctive strategies or patterns in participants' decision rules. There are significant differences in mental model accuracy across these different strategies, and the different strategies account for significant variation in performance. These findings help us understand how variation in mental models and decision making underlies the origins of successful strategies.

Additionally, we find that decision rules stabilize rapidly, which explains why performance plateaus far below the potential achievable level. Rapid stabilization of decision rules is consistent with psychology research on complex problem solving that shows actors learning a new task or solving a novel complex problem quickly automate decision and action rules once they reach functional, satisficing levels of performance (Ericsson, Krampe, and Tesch-Romer, 1993). Our results are also consistent with research that finds managers typically interpret information to reinforce their current mental model rather than challenge and update their beliefs (Barr *et al*., 1992). Similarly, another stream of simulation-based research suggests that in the face of complexity, many firms reach suboptimal decision configuration 'sticking points' from which they do not move (Rivkin, 2000; Rivkin and Siggelkow, 2003).

We did not find evidence that more accurate mental models were more important in the higher complexity decision environment. However, compared with very simple tasks, both of our management simulations were fairly complex. Even the low complexity version of the new product launch simulation includes time delays, nonlinearities, and multiple feedback effects. Perhaps in truly simple competitive environments—with smooth payoff landscapes—mental model accuracy may be less important for achieving high performance outcomes (Gavetti and Levinthal, 2000). There may also be a level of complexity that overwhelms managers' capacity to either accurately infer causal relationships in the business environment or apply their mental models to make effective strategic choices (Rivkin, 2001).

Also, we did not find a positive link between mental model complexity and performance. This is at odds with prior research findings on the benefits of more complex mental models (Lurigio and Carroll, 1985; McNamara *et al*., 2002). However, there are important measurement differences that partially explain why our findings are different. Our focus on causal relationships led to an operationalization of mental model complexity that includes correct as well as incorrect cause-effect inferences. As expected, our results show that more complex mental models—that include incorrect causal inferences—do not enhance performance above simpler, more accurate mental models. We believe much of the prior research has used mental model complexity as a proxy for

DOI: 10.1002/smj

mental model accuracy, and this is not always the case. There is evidence that domain experts generally have more complex knowledge structures than novices (Lurigio and Carroll, 1985). However, expert knowledge is not a direct function of the number of years of experience a decision maker has in a domain.

Limitations and future research

Experimental findings linking differences in mental models, decision rules, and strategies to performance heterogeneity are not conclusive evidence of these links in real competitive environments. External validity is a common concern with experimental studies and ultimately can only be addressed through accumulating a stream of both experimental studies and field research replicating and extending our findings. However, recent meta-analyses comparing effect sizes from lab studies and field research reveals a correlation of 0.73–0.97, suggesting a high degree of generalizability from laboratory to field (Anderson, Lindsay, and Bushman, 1999; Cohen-Charash and Spector, 2001). In the design of our study, we also made choices that we believe contribute to the potential external validity of our findings.

Dynamic decision-making experiments using complex management simulations incorporating feedback, time delays, stock accumulations, and nonlinearities more closely approximate the decision-making environments of senior managers than the experimental tasks typically employed in psychological and judgment and decision-making research. Our management simulation represents a common real world strategic challenge of managing a new product over the entire life cycle (Bass, 1969; Paich and Sterman, 1993; Roberts and Urban, 1988). In addition, decision makers in our studies had access to the same sort of information—through quarterly management reports about their simulated firm—that managers use in making similar decisions in real organizations (e.g., financial and operational reports).

Set against the potential limits to the external validity of our findings are the rigorous internal validity claims afforded by our experimental design. Our research design enabled us to measure attributes of decision makers' mental models such as accuracy of causal inferences. These are notoriously difficult to measure in the field due to uncertainty about the objective cause-effect relationships. While our measure of mental model accuracy is certainly not ideal, the overall fit in the nomological network is supportive of construct validity (Schwab, 1980). A mental model of a problem domain contains direct representations of the entities observed in the environment and simulates the interaction of these entities through operators that predict subsequent events (Larkin, 1983). Our measure of mental model accuracy aims to capture both of these aspects of decision makers' mental models.

We are optimistic that future research will continue to advance the measurement of mental models. An ideal measure would capture the formation and evolution of mental models over time, and would identify how knowledge about causal relationships informs beliefs about gestalt system behavior. There is also an opportunity for future research to identify different components of mental models and examine the conditions under which different sources of inaccuracy are important. In an exploratory analysis of our data, we identified two types of errors that significantly influenced performance in our study. Inferring a causal relationship between two variables when in reality no causal relationship exists is a superstitious belief (Levitt and March, 1988). Omitting a real causal relationship between two variables is a causal blind spot. We found that causal blind spots and superstitious beliefs about the business environment led to lower performance. We need more research investigating the types of misperceptions and errors in mental models that are most damaging.

Future research should assess the generalizability of our findings by testing the relationships between mental models, decision rules, strategies, and performance both in the field and in laboratory experiments across a variety of management contexts and decision makers. Recent developments in measuring knowledge in the field may provide opportunities to accurately estimate knowledge levels in domains where the objectively right answers are not known *a priori* (Borgatti and Carboni, 2007). Prior research also suggests possible ways to operationalize decision environment complexity in field settings (Sutherland, 1980), potentially providing a path for exploring the impact of complexity on mental models, strategic decisions, and performance in the field.

Our study also focuses on individual decision makers and does not explore the enactment process

in organizations where teams of executives come together to make decisions. Firm strategies and decisions are the product of a socio-political process embedded in an organizational setting involving multiple actors (Chattopadhyay *et al*., 1999); however, ultimately it is individuals whose mental models form the substance of such collective deliberations. We believe isolating the cognitive aspects of decision making enables us to build solid micro-foundations before we extend the scope to include social processes.

Our results suggest that addressing deficiencies in mental model accuracy will help improve performance outcomes. Fortunately, knowledge gaps are subject to remedial action. We believe learning laboratories using simulation models of common management challenges represent one promising approach to developing high quality mental models of the deep structures (Gary *et al*., 2008). Recent advances in interactive modeling and simulation tools provide an effective means for representing the causal structure of business and social systems and to learn about these complex, dynamic environments through simulation (Sterman, 2000). More work is also needed to isolate the small set of enduring causal relationships underpinning a wide range of management problems and challenges. Research on interventions to develop reflection and deframing skills to help managers question their own mental models and decision rules are also needed. Such skills may prevent managers and firms from prematurely locking into inaccurate mental models and decision rules (Rivkin and Siggelkow, 2003; Tripsas and Gavetti, 2000).

There are also opportunities for research examining heterogeneity in the decision rules connecting high-level strategies with decision-making processes on the front lines (Cyert and March, 1992; Simon, 1991). Research on decision errors and biases has primarily focused on identifying the mean or modal effects of specific types of errors (Camerer and Lovallo, 1999; Kahneman and Tversky, 2000; Paich and Sterman, 1993; Zajac and Bazerman, 1991). More work is needed to understand the heterogeneity in decision rules and heuristics and how differences in decision rules impact performance. This is particularly important for strategy scholars trying to explain heterogeneity in strategies and performance among firms. Additional research is also called for on the formation of decision rules and the links to mental models to help us better understand the origins of strategy.

Our findings provide much needed empirical evidence that differences in mental model accuracy explain why decision makers adopt different strategies associated with different levels of competitive success. This represents an important step forward and provides a number of opportunities for future research to examine the cognitive aspects of strategy and identify mechanisms to support better strategic thinking and decisions.

ACKNOWLEDGEMENTS

We are grateful for many helpful suggestions from Scott Rockart, John Sterman, Will Mitchell, Rich Burton, Margie Peteraf, and Rich Bettis. We also thank seminar participants at Duke University, MIT, UNC Chapel Hill, Kellogg, and Dartmouth. This paper also benefitted immensely from comments by Associate Editor Rudi Bresser, and two anonymous referees.

REFERENCES

Anderson CA, Lindsay JJ, Bushman BJ. 1999. Research in the psychological laboratory: truth or triviality? *Current Directions in Psychological Science* **8**(1): 3–9.

Anderson JR. 1990. *Cognitive Psychology and its Implications* (3rd edn). Freeman: New York.

Argyris C, Schon D. 1974. *Theory in Practice: Increasing Professional Effectiveness*. Jossey-Bass: San Fransciso.

Atkins PWB, Wood RE, Rutgers PJ. 2002. The effects of feedback format on dynamic decision making. *Organizational Behavior and Human Decision Processes* **88**: 587–604.

Axelrod RM. 1976. *Structure of Decision: The Cognitive Maps of Political Elites*. Princeton University Press: Princeton, NJ.

Bandura A. 1997. *Self-efficacy: The Exercise of Control*. Freeman: New York.

Barr PS, Stimpert JL, Huff AS. 1992. Cognitive change, strategic action and organizational renewal. *Strategic Management Journal*, Summer Special Issue **13**: 15–36.

Bass FM. 1969. A new product growth model for consumer durables. *Management Science* **15**(5): 215–227.

Bettis RA, Prahalad CK. 1995. The dominant logic: retrospective and extension. *Strategic Management Journal* **16**(1): 5–14.

Borgatti SP, Carboni I. 2007. On measuring individual knowledge in organizations. *Organizational Research Methods* **10**(3): 449–462.

Bourgeois LJ. 1985. Strategic goals, perceived uncertainty, and economic performance in volatile environments. *Academy of Management Journal* **28**(3): 548–573.

Camerer C. 1981. General conditions for the success of bootstrapping models. *Organizational Behavior and Human Performance* **27**(3): 411–422.

Camerer C, Lovallo D. 1999. Overconfidence and excess entry: an experimental approach. *American Economic Review* **89**(1): 306–318.

Chase WG, Simon HA. 1973. Perception in chess. *Cognitive Psychology* **4**: 55–81.

Chattopadhyay P, Glick WH, Miller CC, Huber GP. 1999. Determinants of executive beliefs: comparing functional conditioning and social influence. *Strategic Management Journal* **20**(8): 763–789.

Chi M, Feltovich PJ, Glaser R. 1981. Representation of physics knowledge by experts and novices. *Cognitive Science* **5**: 121–152.

Cockburn IM, Henderson RM, Stern S. 2000. Untangling the origins of competitive advantage. *Strategic Management Journal*, October-November Special Issue **21**: 1123–1145.

Cohen-Charash Y, Spector PE. 2001. The role of justice in organizations: a meta-analysis. *Organizational Behavior and Human Decision Processes* **86**(2): 278–321.

Cyert RM, March JG. 1992. *A Behavioral Theory of the Firm* (2nd edn). Blackwell: Malden, MA.

Denrell J, Fang C, Levinthal DA. 2004. From T-mazes to labyrinths: learning from model-based feedback. *Management Science* **50**(10): 1366–1378.

Eden C, Spender J-C (eds). 1998. *Managerial and Organizational Cognition: Theory, Methods, and Research*. Sage: London, UK.

Einhorn HJ, Kleinmuntz DN, Kleinmuntz B. 1979. Linear regression and process-tracing models of judgment. *Psychological Review* **86**(5): 465–485.

Ericsson KA, Krampe TT, Tesch-Romer C. 1993. The role of deliberate practice in the acquisition of expert performance. *Psychological Review* **100**: 363–406.

Gary MS, Dosi G, Lovallo D. 2008. Boom and bust behavior: on the persistence of strategic decision biases. In *The Oxford Handbook of Organizational Decision Making,* Hodgkinson GP, Starbuck WH (eds). Oxford University Press: Oxford, UK; 33–55.

Gavetti G. 2005. Cognition and hierarchy: rethinking the microfoundations of capabilities' development. *Organization Science* **16**(6): 599–617.

Gavetti G, Levinthal D. 2000. Looking forward and looking backward: cognitive and experiential search. *Administrative Science Quarterly* **45**(1): 113–137.

Gavetti G, Levinthal DA, Rivkin JW. 2005. Strategy making in novel and complex worlds: the power of analogy. *Strategic Management Journal* **26**(8): 691–712.

Gentner D, Loewenstein J, Thompson L. 2003. Learning and transfer: a general role for analogical encoding. *Journal of Educational Psychology* **95**(2): 393–408.

Hatten K, Schendel D. 1976. Strategy's role in policy research. *Journal of Economics and Business* **28**(3): 195–202.

Henderson R. 2000. Luck, leadership, and strategy. In *Economics Meets Sociology in Strategic Management* (Volume 17) *Advances in Strategic Management*, Baum JAC, Dobbin F (eds). JAI Press: Stamford, CT; 285–290.

Hodgkinson GP, Bown NJ, Maule AJ, Glaister KW, Pearman AD. 1999. Breaking the frame: an analysis of strategic cognition and decision making under uncertainty. *Strategic Management Journal* **20**(10): 977–985.

Hodgkinson GP, Johnson G. 1994. Exploring the mental models of competitive strategists: the case for a processual approach. *Journal of Management Studies* **31**(4): 525–552.

Hodgkinson GP, Maule AJ, Bown NJ. 2004. Causal cognitive mapping in the organizational strategy field: a comparison of alternative elicitation procedures. *Organizational Research Methods* **7**(1): 3–26.

Huff AS. 1990. *Mapping Strategic Thought*. Wiley: New York.

Jackson SE, Dutton JE. 1988. Discerning threats and opportunities. *Administrative Science Quarterly* **33**(3): 370–387.

Johnson-Laird PN. 1983. *Mental Models: Towards a Cognitive Science of Language, Inference and Consciousness*. Cambridge University Press: Cambridge, UK.

Kahneman D, Tversky A. 2000. *Choices, Values, and Frames*. Cambridge University Press: Cambridge, UK.

Kalish S, Lilien GL. 1986. A market entry timing model for new technologies. *Management Science* **32**(2): 194–205.

Kaplan S, Tripsas M. 2008. Thinking about technology: applying a cognitive lens to technical change. *Research Policy* **37**(5): 790–805.

Ketchen DJ Jr, Shook CL. 1996. The application of cluster analysis in strategic management research: an analysis and critique. *Strategic Management Journal* **17**(6): 441–458.

Larkin J. 1983. The role of problem representation in physics. In *Mental Models*, Gentner D, Stevens A (eds). Erlbaum: Hillsdale, NJ; 75–98.

Levitt B, March JG. 1988. Organizational learning. *Annual Review of Sociology* **14**: 319–340.

Lurigio AJ, Carroll JS. 1985. Probation officers' schemata of offenders: content, development, and impact on treatment decisions. *Journal of Personality and Social Psychology* **48**(5): 1112–1126.

Mahajan V, Muller E, Bass FM. 1990. New product diffusion models in marketing: a review and directions for research. *Journal of Marketing* **54**(1): 1–26.

Mahajan V, Muller E, Bass FM. 1995. Diffusion of new products: empirical generalizations and managerial uses. *Marketing Science* **14**(3): 79–89.

March JG, Simon HA. 1958. *Organizations*. Wiley: New York.

McNamara GM, Luce RA, Tompson GH. 2002. Examining the effect of complexity in strategic group knowledge structures on firm performance. *Strategic Management Journal* **23**(2): 153–170.

Moxnes E. 1998. Not only the tragedy of the commons: misperceptions of bioeconomics. *Management Science* **44**(9): 1234–1248.

Nelson RR, Winter SG. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge, MA.

Norman DA. 1983. Some observations on mental models. In *Mental Models*, Gentner D, Stevens A (eds). Erlbaum: Hillsdale, NJ; 7–14.

Osborne JD, Stubbart CI, Ramaprasad A. 2001. Strategic groups and competitive enactment: a study of dynamic relationships between mental models and performance. *Strategic Management Journal* **22**(5): 435–454.

Paich M, Sterman JD. 1993. Boom, bust, and failures to learn in experimental markets. *Management Science* **39**(12): 1439–1458.

Parker P. 1994. Aggregate diffusion forecasting models in marketing: a critical review. *International Journal of Forecasting* **10**(2): 353–380.

Porac JF, Thomas H, Baden-Fuller C. 1989. Competitive groups as cognitive communities: the case of Scottish knitwear manufacturers. *Journal of Management Studies* **26**(4): 397–416.

Porac JF, Thomas H, Wilson F, Paton D, Kanfer A. 1995. Rivalry and the industry model of Scottish knitwear producers. *Administrative Science Quarterly* **40**(2): 203–227.

Powell MJD. 1998. Direct search algorithms for optimization calculations. *Acta Numerica* **7**: 287–336.

Reger RK, Huff AS. 1993. Strategic groups: a cognitive perspective. *Strategic Management Journal* **14**(2): 103–124.

Rehder B. 2003. Categorization as causal reasoning. *Cognitive Science* **27**(5): 709–748.

Rivkin JW. 2000. Imitation of complex strategies. *Management Science* **46**: 824–844.

Rivkin JW. 2001. Reproducing knowledge: replication without imitation at moderate complexity. *Organization Science* **12**(3): 274–293.

Rivkin JW, Siggelkow N. 2003. Balancing search and stability: interdependencies among elements of organizational design. *Management Science* **49**(3): 290–311.

Roberts JH, Urban GL. 1988. Modeling multiattribute utility, risk, and belief dynamics for new consumer durable brand choice. *Management Science* **34**(2): 167–185.

Rogers E. 1995. *Diffusion of Innovations* (4th edn). Free Press: New York.

Schwab DP. 1980. Construct validity in organizational behavior. In *Research in Organizational Behavior (Volume 2)*, Staw BM, Cummings LL (eds). JAI Press: Greenwich, CT; 3–43.

Sengupta K, Abdel-Hamid TK. 1993. Alternative conceptions of feedback in dynamic decision environments: an experimental investigation. *Management Science* **39**(4): 411–428.

Simon HA. 1991. Bounded rationality and organizational learning. *Organization Science* **2**(1): 125–134.

Sterman JD. 1989a. Misperceptions of feedback in dynamic decision making. *Organizational Behavior and Human Decision Processes* **43**(3): 301–335.

Sterman JD. 1989b. Modeling managerial behavior: misperceptions of feedback in a dynamic decision experiment. *Management Science* **35**(3): 321–339.

Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin/McGraw-Hill: New York.

Sterman JD, Henderson R, Beinhocker ED, Newman LI. 2007. Getting big too fast: strategic dynamics with increasing returns and bounded rationality. *Management Science* **53**(4): 683–696.

Stinchcombe A. 2000. On equilibrium, organizational form, and competitive strategy. In *Economics Meets Sociology in Strategic Management (Volume 17) Advances in Strategic Management*, Baum JAC, F Dobbin F (eds). JAI Press: Greenwich,CT; 271–284.

Sutcliffe KM. 1994. What executives notice: accurate perceptions in top management teams. *Academy of Management Journal* **37**(5): 1360–1378.

Sutherland JW. 1980. A quasi-empirical mapping of optimal scale of enterprise. *Management Science* **26**(10): 963–981.

Tripsas M, Gavetti G. 2000. Capabilities, cognition, and inertia: evidence from digital imaging. *Strategic Management Journal*, October–November Special Issue **21**: 1147–1161.

Verbeke G, Molenberghs G. 2000. *Linear Mixed Models for Longitudinal Data*. Springer Verlag: New York.

Walsh JP. 1995. Managerial and organizational cognition: notes from a trip down Memory Lane. *Organization Science* **6**: 280–321.

Weick KE. 1990. Cartographic myths in organization. In *Mapping Strategic Thought*, Huff AS (ed). John Wiley & Sons: Chichester, UK; 1–10.

Wood RE, Bandura A, Bailey T. 1990. Mechanisms governing organizational performance in complex decision-making environments. *Organizational Behavior and Human Decision Processes* **46**: 181–201.

Zajac EJ, Bazerman MH. 1991. Blind spots in industry and competitor analysis: implications of interfirm (mis)perceptions for strategic decisions. *Academy of Management Review* **16**(1): 37–56.

APPENDIX A: SEGMENT FROM THE FIRST SET OF KNOWLEDGE QUESTIONS ABOUT BIVARIATE CAUSAL RELATIONSHIPS

$X \xrightarrow{S} Y$

This arrow indicates that an increase in X results in an increase in Y above what it would have been (all else being equal). On the other hand, a decrease in X results in a decrease in Y below what it would have been (all else being equal). X and Y move in the SAME direction.

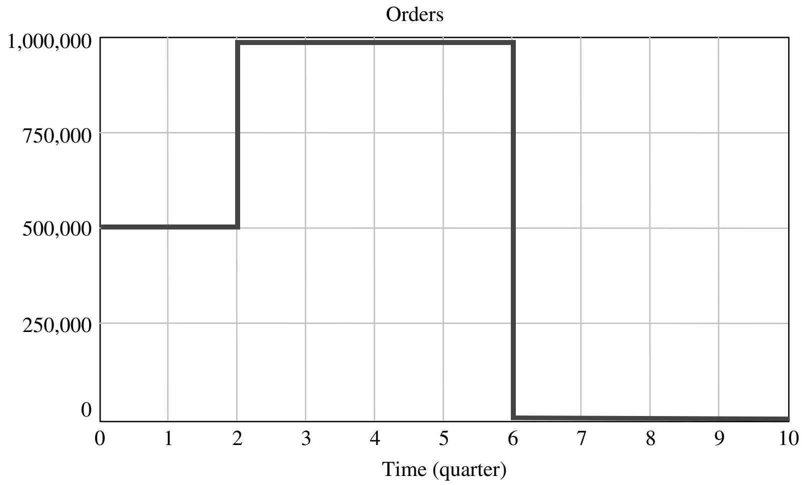
$X \xrightarrow{O} Y$

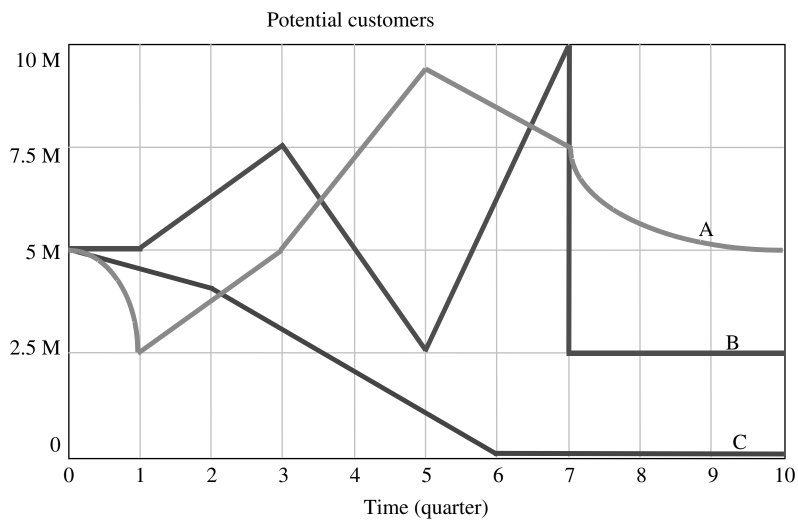
In contrast, this arrow indicates X and Y move in the OPPOSITE direction. For example, an increase in X results in a decrease in Y below what it would have been (all else being equal). On the other hand, a decrease in X results in an increase in Y above what it would have been (all else being equal).

Think about the relationships between these variables that you believe are embedded in the simulator. Relying only on your experience with the simulated firm, draw the appropriate influence arrow(s) for each variable pair and indicate whether the causal influence is in the same or opposite direction using an 'S' or 'O' at the end of the arrow. Identify any cases in which there is two-way dependency between the variables by drawing the appropriate arrows representing the two-way loop of influence. Focus only on direct relationships and ignore any intervening variables that may result in indirect influence arrows. If there is no direct relationship between the variable pair, write 'NONE' between the two variables. If you do not have any idea about the correct answer, then write 'Do not know' instead of randomly guessing.

1. Orders	Backlog
2. Shipments	Backlog
3. Backlog	Delivery delay

DOI: 10.1002/smj





APPENDIX B: EXAMPLE QUESTION FROM THE SECOND SET OF KNOWLEDGE QUESTIONS ABOUT GRAPHICAL SCENARIOS

Using the time path of total industry orders provided in the top graph below, select the letter of the appropriate time path for industry potential customers on the bottom graph. Circle D if none of the lines in the bottom graph shows the correct time path. Assume the initial value of industry potential customers is 5 million at time 0 and that no other variables affect industry potential customers over this time horizon.

DOI: 10.1002/smj

APPENDIX C: EXAMPLE QUESTIONS ASSESSING DEEP STRUCTURE ACCURACY

Following are seven examples about bivariate causal relationships used to measure deep structure accuracy. See Appendix A for the instructions given to participants for answering these questions. Note that these questions appeared randomly throughout the knowledge test and, therefore, the numbers along the left side of the table below do not reflect the order of the questions in the full knowledge test. The remaining four items of the deep structure accuracy measure are graphical scenario questions covering a subset of the same relationships. The graphical scenario example question in Appendix B is one of these items.

1 Potential customers	Orders
2 Potential customers	Reentry as potential customers
3 Potential customers	Price
4 Installed customer base	Shipments
5 Installed customer base	Reentry as potential customers
6 Installed customer base	Word-of-mouth effect
7 Orders	Word-of-mouth effect